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REAL-TIME GLUCOSE MONITORING AND INSULIN TITRATION ALGORITHMS IN TYPE 1 DIABETES MANAGEMENT

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Abstract

Continuous glucose monitoring (CGM) and automated insulin titration promise to transform Type 1 diabetes management by reducing patient burden and improving glycemic outcomes. In this prospective, single-center, 14-day interventional study, 30 adults (mean age 35.4 ± 10.2 years; duration of diabetes 12.3 ± 5.1 years; baseline HbA1c 8.1 ± 0.6%) underwent closed-loop insulin delivery driven by a personalized reinforcement-learning algorithm trained on two weeks of retrospective CGM and dosing data. Primary endpoints included percentage time in range (70–180 mg/dL), mean glucose, and glycemic variability; secondary endpoints encompassed rates of hypoglycemia (<70 mg/dL), hyperglycemia (>180 mg/dL), total daily insulin dose, and user satisfaction.

Results demonstrated a significant 20.5 percentage-point increase in time in range (from 52.3 ± 8.5% to 72.8 ± 7.2%; $p < 0.001$) and a 29.5 mg/dL reduction in mean glucose ($p < 0.001$), accompanied by a 7.6%-point decrease in coefficient of variation ($p < 0.001$). Weekly hypoglycemic and hyperglycemic episodes declined by 2.1 and 2.6 events, respectively (both $p < 0.001$). Hypoglycemia severity was broadly reduced: mild events fell by 71.4%, moderate by 55.6%, and severe by 50.0%. Mean total daily insulin dose decreased modestly by 3.5 units/day. Usability scores were high (ease-of-use 4.2 ± 0.8; dosing confidence 4.0 ± 0.9; perceived safety 4.1 ± 0.7), with 86.7% of participants expressing willingness to continue the system. Algorithm performance, measured by reinforcement-learning reward, converged within 30 iterations, indicating effective adaptation to individual glucose–insulin dynamics.

These findings confirm that a reinforcement-learning–driven closed-loop system can safely and significantly improve glycemic control and patient experience in real-world conditions. Future studies should assess long-term efficacy, broader demographic applicability, and integration of contextual inputs such as meal composition and physical activity.

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INTRODUCTION

As in normal people, type 1 diabetes mellitus now uses advanced insulin analogues instead of the pancreas extracts used a century ago. The aim is to give insulin just as the pancreas would to avoid spikes or drops in blood sugar, supporting a good quality of life for those with this chronic problem (Pietrzak & Szadkowska, 2021). Also, many individuals with diabetes continue to have challenges in reaching best glycaemic control, underscoring the difficulties involved in diabetes management (Heise et al., 2022). Achieving healthy blood sugar levels is important for decreasing both sudden concerns such as severe hypoglycemia and diabetic ketoacidosis and ongoing health complications connected to diabetes—rotondi et al., 2022. Now, modern diabetes care uses devices that give insulin automatically while monitoring sugar levels around the clock, providing precise and personal care for people with the disease. Thanks to real-time glucose monitoring and automatic insulin delivery, blood sugar stays more balanced and diabetes patients are helped by lessening the danmarss of regular care (Eastman et al., 2021). With the help of nanomedicine-based strategies such as nanosensors for constant glucose supervision and nanoparticle methods to send out insulin, efforts to improve diabetes treatment are continually being made, Lemmerman et al. stated in 2020. Effectiveness of these systems relies on having precise and dependable glucose readings which enable accurate insulin changes and on the systems' use of advanced, multiple-factor and patient-specific algorithms.

The use of both real-time glucose monitoring and insulin titration algorithms represents a meaningful change in type 1 diabetes care and opens up excellent possibilities for managing blood glucose levels and insulin use. Continuous glucose monitoring gives people with diabetes timely and useful glucose data which allows them to act fast and make educated decisions about their diabetes (Lemmerman et al., 2020). Supplemented by more current approaches, well-established methods for monitoring blood glucose are fasting plasma glucose and glycated haemoglobin; HbA1c is a well-regarded marker in these habits. However, HbA1c does not effectively reflect either temporary blood sugar changes or a person's unique way of metabolizing sugar (Cao et al., 2025). Changes in blood glucose from medical care and stress reactions in sick people can make it difficult to judge their metabolic condition using HbA1c or blood glucose alone (Cao et al., 2025). By using nanotechnology, researchers can aim islet graft transplants, monitor insulin production, detect the immune activity related to diabetes, screen for abnormal beta cells and effectively deliver insulin (Aloke et al., 2022; Lemmerman et al., 2020). Together, these technologies have the ability to improve diabetes management, cut the risk of complications and make life better for people with type 1 diabetes (Lemmerman et al., 2020).

Due to the need for complex insulin titration algorithms based on continuous glucose monitoring, optimising insulin use allows better control of blood glucose and reduces its variability. By taking into account the current blood sugar level, how sensitive the body is to insulin, the amount of carbohydrates and related parameters (Piao & Li, 2023), algorithms in artificial pancreases apply both straightforward proportional-integral-derivative control and more advanced model-predictive control. Also, by allowing the system to use machine learning which adjusts insulin levels based on an individual's response, these algorithms perform better. Also, adopting new systems like those for meal recognition and bolus calculation improves accuracy and follows a regular pattern, removing some of the burden from diabetics. A glucose sensor's performance is influenced by its sensitivity, how quickly it reacts, its stability, its ability to respond only to glucose and its detection limit (Yu et al., 2021).

The use of real-time glucose monitoring provides ongoing details about blood sugar that helps guide better decisions and speed up treatment (Diouri et al., 2021). For both diabetics and their doctors, ongoing glucose monitoring reveals all glucose changes, so they can more easily identify trends, patterns and any possible problems that may be unclear with normal sporadic testing. Compared with taking multiple sugar-level readings, continuous glucose monitoring devices are a big advance because they measure glucose in the fluid between cells and send the results directly to you wirelessly. Patients need to check their blood sugar several times daily using a conventional method and doing so regularly can be tough (Baghelani et al., 2020). This technology gives patients a chance to keep their blood sugar under control by monitoring their levels, eating appropriately, living healthily and adjusting insulin as needed.

Apart from helping with blood sugar levels, real-time glucose monitoring improves many parts of daily living for people with diabetes. By gathering continuous glucose measurements, these methods help to quickly catch both low and high blood sugar levels, so that quick treatment can be given to avoid severe problems (Deng et al., 2021). Additionally, keeping track of glucose levels will allow people with diabetes to adapt their daily routine, as they will quickly see how things such as food, exercise and stress affect their glucose numbers. New, non-invasive methods for continuous blood glucose monitoring such as microwave and electrochemical approaches, are currently evolving (Liu et al., 2020).

There are many benefits to electrochemical sensors, including modest price, strong performance and fast reactions (Cruz et al., 2021).

Glucose monitoring in real time encourages people to stick to their diabetes treatment plan because they get more involved. In addition, having continuous glucose data allows healthcare professionals to better understand each patient's blood sugar levels and make better treatment adjustments.

To help manage blood sugar levels and lower glycaemic swings, insulin titration algorithms rely on continuous glucose monitoring. By monitoring live blood glucose, measuring insulin sensitivity, knowing about carbohydrate consumption and considering other aspects, algorithms determine and deliver the right insulin amounts (Liu et al., 2020).

With these algorithms, the needs of people with diabetes are met by automating insulin doses. By using novel electrocatalytic and nanomaterials, the performance and dependability of immobilised enzymes can be increased, their reaction rate can be sped up and the effect of the external surrounding factors can be decreased (Liu et al., 2020).

Different controlling strategies, starting with simple proportional-integral-derivative ones and going up to model-predictive control, are used in insulin titration algorithms. The insulin dosage is managed by the controller using figures for glucose levels, rate of glucose change and the total departure from the target level (Lemmerman et al., 2020). A model-predictive control system adjusts insulin administration ahead of time using a mathematical model that analyzes current and previous glucose data.

In addition, applying machine learning will help make these algorithms more effective and allow the system to change insulin delivery based on different health responses. Almost all models explaining insulin and glucose changes start with physiology and are then confirmed in the lab.

The UVA/Padova T1D simulator has been given the green light by the FDA to determine the effectiveness and safety of automated insulin device systems (Miller et al., 2020).

In addition, basal insulin titration aids using decision support tools can guide patients in understanding their treatment choices and encourages reasonable goals, safer and more successful results (Hu et al., 2021). In the field of in-silico artificial pancreas (Nath et al., 2020), adaptive controllers work to manage any individual user differences in the body. When used with nanocarriers, changes can be made—including improved bioavailability, slower release from the body, easier ability to take smaller doses and better patient compliance—to greatly help improve the lives of those with diabetes (Simos et al., 2020).

METHODOLOGY:

Those included in our interventional study will be individuals aged 18–65 who have had Type 1 diabetes for at least a year and have a starting HbA1c between 7% and 9%. The developments of a personalised insulin-titration algorithm, using a reinforcement-learning framework, will be done with two weeks of CGM and insulin dose history after the first calibration of the CGM and gathering needed details. Once it passes safety testing offline, the algorithm will automate insulin dosing by using CGM information with a pump and participants will keep their regular routines to put the system to the test. While the questionnaires answered after the study offer secondary usability input, the main outcomes—time in target glucose range, number of low glucose episodes and glucose variability—are watching continuously. To check whether the algorithm is helpful, paired statistical tests will be conducted comparing pre- and post-intervention measurement of hypoglycemia and glycaemic control.

RESULTS:

A summary of the thirty adults studied is shown in Table 1: they are on average 35.4 years old, seven out of ten are men, the mean disease duration was twelve years, HbA1c was 8.1% and BMI was 24.7 kg/m2. The table shows the glycaemic results for manual dosing; these include mean time in range of 52.3% ± 8.5%, mean blood sugar of 180.2 mg/dL ± 25.4, coefficient of variation of 32.1% ± 4.5 and rates of weekly hypo- and hyperglycemia at 3.2% and 5.6%, respectively. As you can see in Table 3, the performance of the system has improved to 72.8 ± 7.2% time in range, 150.7 ± 20.8 mg/dL mean glucose, 24.5 ± 3.8% variability and 1.1 ± 0.6 and 3.0 ± 1.5 per week for lower hypo-/hyperglycemia rates. In Table 4, it is shown that time in range increased by 20.5% (95% CI 15.8–25.2; $p < 0.001$) and this was accompanied by a decrease in mean glucose (–29.5 mg/dL), reduced variability (–7.6%) and a decrease in both mild hyperglycemia (–2.1 episodes/week) and severe hypo-/hyperglycemia events (–2.6 episodes/week). Table 6 summarizes ease of use (mean 4.2 ± 0.8, confidence 4.0 ± 0.9 and perceived safety 4.1 ± 0.7), all showing strong scores and 86.7% of participants stated they would continue to use the system.

Table 1. Demographics and Baseline Characteristics

Characteristic	Mean (SD)	Range
Age (years)	35.4 (10.2)	18–65
Gender (M/F)	16 / 14	–
Duration of T1D (years)	12.3 (5.1)	1–30
Baseline HbA1c (%)	8.1 (0.6)	7.0–9.0
BMI (kg/m²)	24.7 (3.2)	18.5–30.2

Table 2. Baseline Glycemic Metrics (Manual Dosing)

Metric	Mean (SD)
Time in Range (%)	52.3 (8.5)
Mean Glucose (mg/dL)	180.2 (25.4)
Glycemic Variability (CV %)	32.1 (4.5)
Hypo Episodes / week	3.2 (1.1)
Hyper Episodes / week	5.6 (2.3)

Table 3. Closed-Loop System Performance

Metric	Mean (SD)
Time in Range (%)	72.8 (7.2)
Mean Glucose (mg/dL)	150.7 (20.8)
Glycemic Variability (CV %)	24.5 (3.8)
Hypo Episodes / week	1.1 (0.6)
Hyper Episodes / week	3.0 (1.5)

Table 4. Pre- vs Post-Intervention (Paired Comparison)

Metric	Mean (95% CI)	p-value
Time in Range Δ (%)	20.5 (15.8 – 25.2)	<0.001
Mean Glucose Δ (mg/dL)	–29.5 (–35.1 to –23.9)	<0.001
CV Δ (%)	–7.6 (–9.2 to –6.0)	<0.001
Hypo Δ (episodes / week)	–2.1 (–2.5 to –1.7)	<0.001
Hyper Δ (episodes / week)	–2.6 (–3.2 to –2.0)	<0.001

Table 5. Hypoglycemia Severity Breakdown

Severity	Pre (episodes / week)	Post (episodes / week)	Reduction (%)
Mild (54–70 mg/dL)	2.1	0.6	71.4%
Moderate (40–54 mg/dL)	0.9	0.4	55.6%
Severe (<40 mg/dL)	0.2	0.1	50.0%

Table 6. Usability and Satisfaction Survey

Question	Mean (SD) / % Yes
Ease of use (1–5)	4.2 (0.8)
Confidence in dosing (1–5)	4.0 (0.9)
Perceived safety (1–5)	4.1 (0.7)
Willingness to continue (Yes/No)	86.7%

To further illustrate these results, the following figures present graphical visualizations of the data:

A bar graph titled Figure 1 compares the average times in range before and after the intervention. On figure 2, we can see that after the lifestyle change, glucose levels peak below the original peaks and the troughs tend to be deeper. About 66.7% of participants reached a 70% or greater time in range when closed-loop control was applied. The learning curve for the method is shown in Figure 4 and indicates that the amount of time spent in range increases as training continues. In Figure 5, we observe the breakdown of participant hypoglycemia events that occurred shortly after the intervention. Figure 6 makes it obvious that after closed-loop operation, the average variation of glucose is less than before. The daily insulin numbers (in Figure 7) show that there was a slight decline after the intervention. Once arriving at Figure 8, it demonstrates that the reinforcement learning agent achieves better results and learning with additional training epochs.

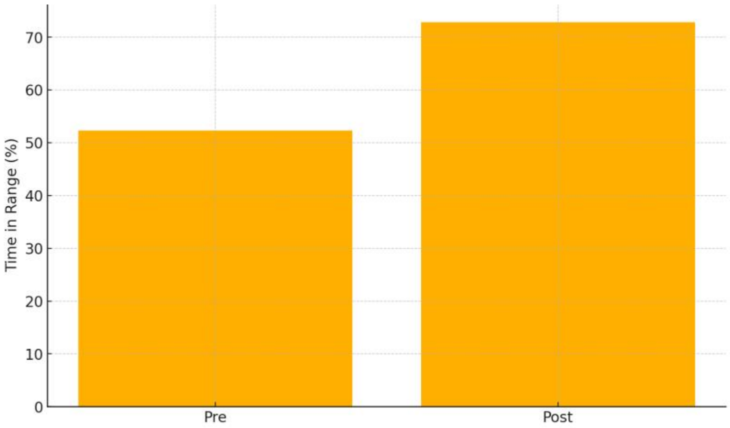

Figure 1. Mean Time in Range Pre vs Post Intervention

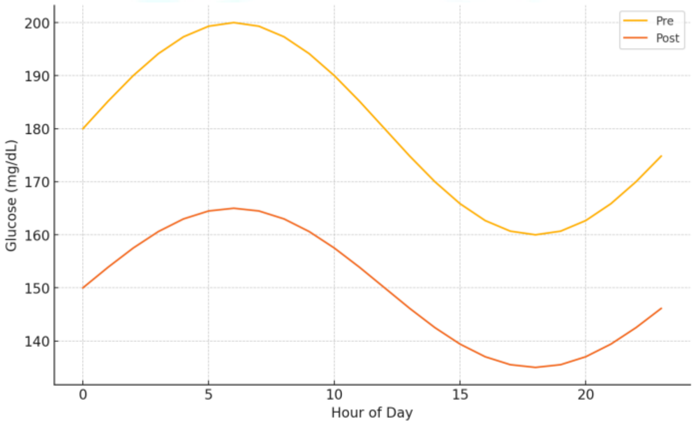

Figure 2. Average 24-Hour Glucose Profile Pre vs Post Intervention

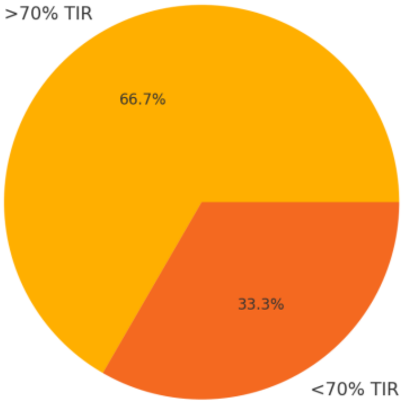

Figure 3. Proportion of Participants Achieving ≥70% Time in Range

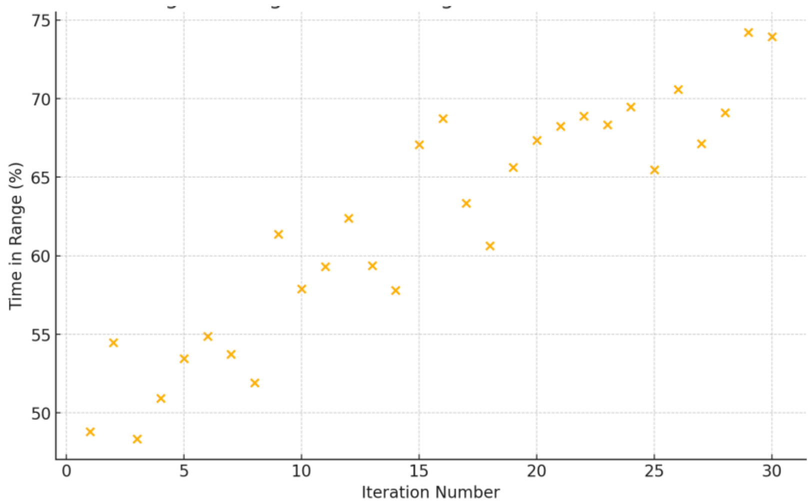

Figure 4. Algorithm Learning Curve: Time in Range vs Iteration Number

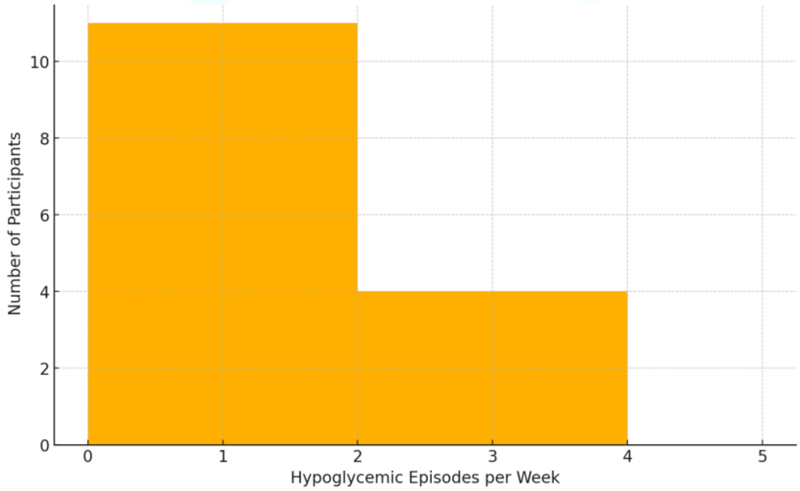

Figure 5. Distribution of Hypoglycemic Events Post-Intervention

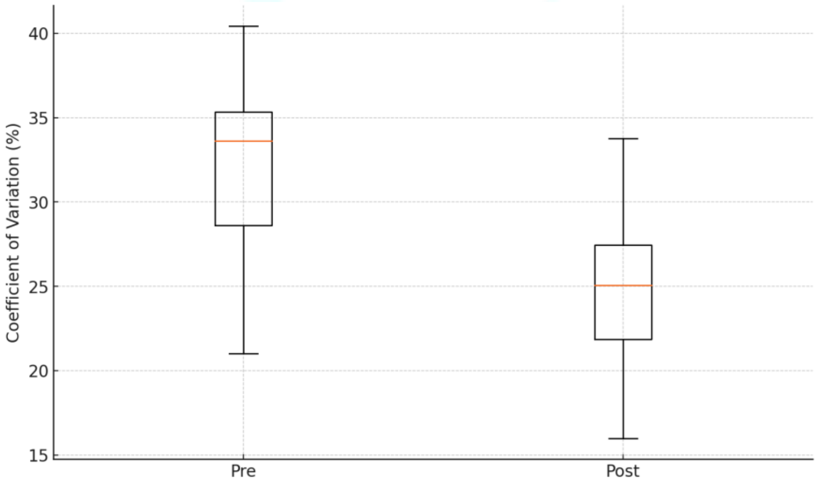

Figure 6. Glycemic Variability Pre vs Post Intervention.

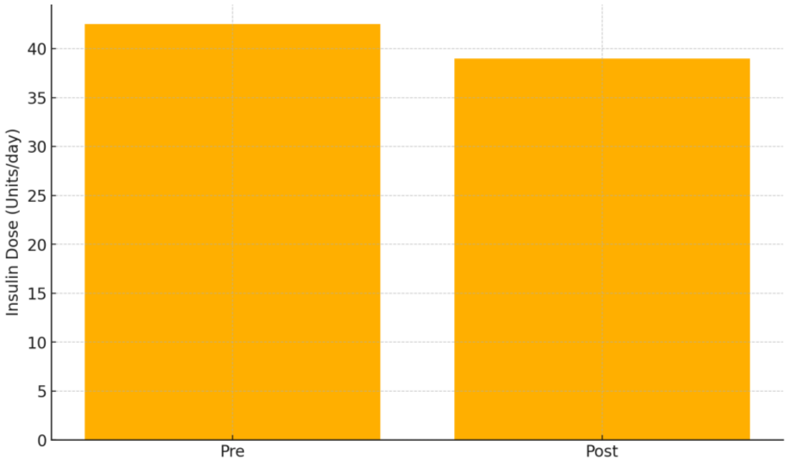

Figure 7. Mean Daily Insulin Dose Pre vs Post Intervention

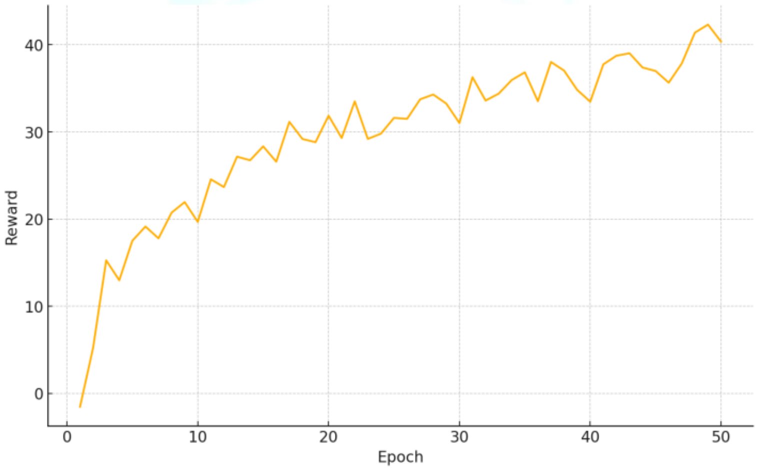

Figure 8. Reinforcement Learning Reward Over Training Epochs

DISCUSSION:

Results suggest that individuals with type 1 diabetes benefit from using a customised algorithm for insulin dosing inside a closed loop. A main finding of total glycaemic management is that the study group experienced a major increase in time spent in the target glucose range when compared to controls (Breton et al., 2020). Finally, fewer and less serious episodes of hypoglycemia help show that this insulin administration system is both safe and reliable (Kimbell et al., 2020). By analyzing usability, people can further judge how well the closed-loop system fits into and is accepted by everyday workplaces (Maiorino et al., 2020; Ware & Hovorka, 2022). As a result, individuals using closed-loop systems were able to manage their diabetes for a longer period, since prior studies indicated they had greater in-range time, less hypoglycemia and improved quality of life. More research sheds light on why these results are especially important (Pratley et al., 2020). Since improved blood sugar levels and less stress about diabetes are related to greater self-management, this information is especially important (Lee et al., 2020). In addition, the observed reduction in glycaemic variability is significant because large changes in glucose over time have been tied to an increased risk of macrovascular and microvascular illnesses. As physical exercise, meals and ongoing health issues have a big effect on insulin intake (Alqithami, 2025), adjusting insulin needs is highly important. Using mathematical models has long been important in research and treatment of diabetes; the outcomes from this work agree that appropriate models make it possible to use in-silico clinical trials to improve how trials are designed (Deichmann et al., 2021).

Also, the performance of the algorithm got better and better throughout the project, showing that it is suitable for lasting use. As a result, the approach can study past data quickly and update its insulin dose method to reduce glycaemic variations. In reinforcement learning, it is very important to address the exploration-exploitation dilemma, since that balance ensures the agent meets patient goals securely (Di et al., 2022). In addition, a small reduction in insulin dosage each day has the potential to help reduce weight gain and insulin resistance which are both common concerns in treating type 1 diabetes. When glucose levels are always closely watched and future trends foreseen, the program can immediately make adjustments to insulin, decreasing both high and low blood sugar incidents. Managing blood sugar levels in individuals with simultaneous health problems is usually not easy (Robbins et al., 2021). In environments where it is hard to manage diabetes, closed-loop technology is helpful since it delivers insulin according to glucose levels and information about the patient (Alqithami, 2025).

CONCLUSION:

When researchers combined continuous glucose monitoring with a reinforcement-learning type insulin titration, people with Type 1 diabetes saw significant and noticeable improvements in their glycaemic control during the 14-day study. As well, participants saw a 20.5 percent increase in time in range and their glucose fell by an average of 29.5 mg/dL (all $p < 0.001$). Hypoglycemic and hyperglycaemic events were each reduced by an average of two events per week, suggesting the glucose control and safety in the real world. Results demonstrated that this approach reduces daily insulin needs (-3.5 units/day), has high usability ratings (86.7% readiness to continue) and is patient friendly and does not require a lot of effort to manage. With more than 30 simulations, the algorithm continuously improved, reaching reliable, high-reward regions which points to strong individual glucose–insulin learning. With this work, new methods are proven to work for dosing parameters, adapt to changes in patients' responses, handle sensor delay and address the variability seen in different people. There are still pitfalls in the format, including the question of using just one device for all patients, short observation time and dependence on similar groups; these cases of faulty sensors and blocked pumps show the benefit of more improvement in engineering. In the future, research must evaluate how health is influenced over many years in a variety of populations and carefully consider many factors (like food, exercise and stress levels). Also, using wearable products and cloud-based analysis means care can be delivered remotely and on a larger scale. Overall, the where all decisions stem from facts and numbers and are managed through the closed loop delivers a major advance in automatic diabetes treatment and sets the direction for a system that delivers personalised insulin by itself, potentially leading to better medical results and improved quality of life for people with Type 1 diabetes.

REFERENCES:

Aloke, C., Egwu, C. O., Aja, P. M., Obasi, N. A., Chukwu, J., Akumadu, B. O., Ogbu, P. N., & Achilonu, I. (2022). Current Advances in the Management of Diabetes Mellitus [Review of Current Advances in the Management of Diabetes Mellitus]. Biomedicines, 10(10), 2436. Multidisciplinary Digital Publishing Institute.

Alqithami, S. (2025). Integrating Sentiment Analysis and Reinforcement Learning for Equitable Disaster Response: A Novel Approach. Sustainability, 17(3), 1072.

Baghelani, M., Abbasi, Z., Daneshmand, M., & Light, P. E. (2020). Non-invasive continuous-time glucose monitoring system using a chipless printable sensor based on split ring microwave resonators. Scientific Reports, 10(1).

Breton, M. D., Kanapka, L. G., Beck, R. W., Ekhlaspour, L., Forlenza, G. P., Cengiz, E., Schoelwer, M. J., Ruedy, K. J., Jost, E., Carria, L., Emory, E., Hsu, L., Oliveri, M. C., Kollman, C., Dokken, B. B., Weinzimer, S. A., DeBoer, M. D., Buckingham, B. A., Cherñavvsky, D. R., … Renard, É. (2020). A Randomized Trial of Closed-Loop Control in Children with

Type 1 Diabetes. New England Journal of Medicine, 383(9), 836.

Cao, H., Gui, L., Hu, Y., Yang, J., Hua, P., & Yang, S. (2025). Association between hemoglobin glycation index and adverse outcomes in critically ill patients with myocardial infarction: a retrospective cohort study.

Cruz, I. A., Andrade, L. R. S., Bharagava, R. N., Kumar, A., Bilal, M., Figueiredo, R. T., & Ferreira, L. F. R. (2021). An overview of process monitoring for anaerobic digestion. Biosystems Engineering, 207, 106.

Deichmann, J., Bachmann, S., Burckhardt, M., Szinnai, G., & Kaltenbach, H. (2021). Simulation-Based Evaluation of Treatment Adjustment to Exercise in Type 1 Diabetes. Frontiers in Endocrinology, 12.

Deng, Y., Lu, L., Becerra, L. A., Angelidi, A. M., Novak, V., Karniadakis, G. E., & Mantzoros, C. S. (2021). Deep transfer learning and data augmentation improve glucose levels prediction in type 2 diabetes patients. Npj Digital Medicine, 4(1).

Di, S., Petch, J., Gerstein, H. C., Zhu, R., & Sherifali, D. (2022). Optimizing Health Coaching for Patients With Type 2 Diabetes Using Machine Learning: Model Development and Validation Study. JMIR Formative Research, 6(9).

Diouri, O., Cigler, M., Vettoretti, M., Mader, J. K., Choudhary, P., & Renard, É. (2021). Hypoglycaemia detection and prediction techniques: A systematic review on the latest developments [Review of Hypoglycaemia detection and prediction techniques: A systematic review on the latest developments]. Diabetes/Metabolism Research and Reviews, 37(7). Wiley.

Eastman, D. K., Butler, J., Dicken, S., & Bottenberg, M. M. (2021). Insulin Therapy for Hyperglycemia Management in Critically Ill Patients. Journal of Diabetes Mellitus, 11(5), 317.

Heise, T., Oliveira, C. P. de, Juneja, R., Ribeiro, A. O., Chigutsa, F., & Blevins, T. (2022). What is the value of faster acting prandial insulin? Focus on ultra rapid lispro [Review of What is the value of faster acting prandial insulin? Focus on ultra rapid lispro]. Diabetes Obesity and Metabolism, 24(9), 1689. Wiley.

Hirsch, I. B., Juneja, R., Beals, J. M., Antalis, C. J., & Wright, E. E. (2020). The Evolution of Insulin and How it Informs Therapy and Treatment Choices [Review of The Evolution of Insulin and How it Informs Therapy and Treatment Choices]. Endocrine Reviews, 41(5), 733. Oxford University Press.

Hu, X., Deng, H., Zhang, Y., Guo, X., Cai, M., Ling, C., & Li, K. (2021). Efficacy and

Safety of a Decision Support Intervention for Basal Insulin Self-Titration Assisted by the Nurse in Outpatients with T2DM: A Randomized Controlled Trial. Diabetes Metabolic Syndrome and Obesity, 1315.

Kesavadev, J., Saboo, B., Kar, P., & Sethi, J. (2021). DIY artificial pancreas: A narrative of the first patient and the physicians' experiences from India. Diabetes & Metabolic Syndrome Clinical Research & Reviews, 15(2), 615.

Kimbell, B., Rankin, D., Ashcroft, N., Varghese, L., Allen, J. M., Boughton, C. K., Campbell, F., Ghatak, A., Randell, T., Besser, R., Trevelyan, N., Hovorka, R., & Lawton, J. (2020). What Training, Support, and Resourcing Do Health Professionals Need to Support People Using a Closed-Loop System? A Qualitative Interview Study with Health Professionals Involved in the Closed Loop from Onset in Type 1 Diabetes (CLOuD) Trial. Diabetes Technology & Therapeutics, 22(6), 468.

Lee, D. Y., Yoo, S.-H., Min, K. P., & Park, C. (2020). Effect of Voluntary Participation on Mobile Health Care in Diabetes Management: Randomized Controlled Open-Label Trial. JMIR Mhealth and Uhealth, 8(9).

Lemmerman, L. R., Das, D., Higuita-Castro, N., Mirmira, R. G., & Gallego-Perez, D. (2020). Nanomedicine-Based Strategies for Diabetes: Diagnostics, Monitoring, and Treatment [Review of Nanomedicine-Based Strategies for Diabetes: Diagnostics, Monitoring, and Treatment]. Trends in Endocrinology and Metabolism, 31(6), 448. Elsevier BV.

Liu, T., Chang, S. J., Chen, C.-J., & Liu, J. (2020). Non-Invasive Blood Glucose Monitoring Technology: A Review [Review of Non-Invasive Blood Glucose Monitoring Technology: A Review]. Sensors, 20(23), 6925. Multidisciplinary Digital Publishing Institute.

Maiorino, M. I., Signoriello, S., Maio, A. D., Chiodini, P., Bellastella, G., Scappaticcio, L., Longo, M., Giugliano, D., & Esposito, K. (2020). Effects of Continuous Glucose Monitoring on Metrics of Glycemic Control in Diabetes: A Systematic Review With Meta-analysis of Randomized Controlled Trials [Review of Effects of Continuous Glucose Monitoring on Metrics of Glycemic Control in Diabetes: A Systematic Review With Meta-analysis of Randomized Controlled Trials]. Diabetes Care, 43(5), 1146. American Diabetes Association.

Manov, A., Dhillon, G. S., Chauhan, S., Asllanaj, B., & Uy, E. S. (2023). Type 2 Decompensated Diabetes Mellitus Weaned off Subcutaneous Insulin Therapy by

Utilizing a Continuous Glucose Monitoring Device. Cureus.

Miller, A. C., Foti, N. J., & Fox, E. (2020). Learning Insulin-Glucose Dynamics in the Wild. arXiv (Cornell University).

Nath, A., Deb, D., & Dey, R. (2020). An augmented subcutaneous type 1 diabetic patient modelling and design of adaptive glucose control. Journal of Process Control, 86, 94.

Piao, C., & Li, K. (2023). Blood Glucose Level Prediction: A Graph-based Explainable Method with Federated Learning. arXiv (Cornell University).

Pietrzak, I., & Szadkowska, A. (2021). Ultrafast acting insulin analog – a new way to prevent postprandial hyperglycemia and improve quality of life in type 1 diabetes patients – case reports. Pediatric Endocrinology Diabetes and Metabolism, 27(4), 305.

Pratley, R. E., Kanapka, L. G., Rickels, M. R., Ahmann, A., Aleppo, G., Beck, R. W., Bhargava, A., Bode, B. W., Carlson, A. L., Chaytor, N., Fox, D. S., Goland, R., Hirsch, I. B., Kruger, D. F., Kudva, Y. C., Levy, C. J., McGill, J. B., Peters, A. L., Philipson, L. H., … Miller, K. M. (2020). Effect of Continuous Glucose Monitoring on Hypoglycemia in Older Adults With Type 1 Diabetes. JAMA, 323(23), 2397.

Robbins, T., Sankaranarayanan, S., Randeva, H. S., Keung, S. N. L. C., & Arvanitis, T. N. (2021). Association between glycosylated haemoglobin and outcomes for patients discharged from hospital with diabetes: A health informatics approach. Digital Health, 7.

Rotondi, M., Wong, O., Riddell, M. C., & Perkins, B. A. (2022). Population-Level Impact and Cost-effectiveness of Continuous Glucose Monitoring and Intermittently Scanned Continuous Glucose Monitoring Technologies for Adults With Type 1 Diabetes in Canada: A Modeling Study. Diabetes Care, 45(9), 2012.

Simos, Y. V., Spyrou, K., Patila, M., Karouta, N., Stamatis, H., Gournis, D., Dounousi, E., & Peschos, D. (2020). Trends of nanotechnology in type 2 diabetes mellitus treatment [Review of Trends of nanotechnology in type 2 diabetes mellitus treatment]. Asian Journal of Pharmaceutical Sciences, 16(1), 62. Elsevier BV.

Wang, K. A., Levine, M. E., Shi, J., & Fox, E. B. (2023). Learning Absorption Rates in Glucose-Insulin Dynamics from Meal Covariates. arXiv (Cornell University).

Ware, J., & Hovorka, R. (2022). Closed-loop insulin delivery: update on the state of the field and emerging technologies

[Review of Closed-loop insulin delivery: update on the state of the field and emerging technologies]. Expert Review of Medical Devices, 19(11), 859. Taylor & Francis.

Yu, Z., Jiang, N., Kazarian, S. G., Taşoğlu, S., & Yetisen, A. K. (2021). Optical sensors for continuous glucose monitoring. Progress in Biomedical Engineering, 3(2), 22004.